1 Introduction

1.1 The philological problem

In the tradition of ancient Greek texts it sometimes happens that, due to a number of different reasons a text is credited incorrectly to a certain author. It is the—sometimes very difficult—task of classical philology to detect these errorneous assignments and, if possible, to correct them. The methods used for this task and the results achieved by them are often subject of strong criticism either because the methods are considered inadequate or because the results are doubted for some reason.

One of the methods commonly used consists in searching for special stylistic properties of a given text and comparing them with the personal style of possible Greek authors of the text in question. By these means researchers aim at matching properties of the text with the characteristics of a given writer in order to declare him the author for whom they have searched, conversely, or at finding enough contradictions between the text's and the writer's stylistic properties to be able to negate the authorship of the writer.

One special technique is called "stylometry". It makes use of several methods from mathematical statistics. More specifically, it uses statistical tests to reject a proposed hypothesis by arguing with quantitative data gained from the text and writer's work.

We want to use stylometry to investigate the authenticity of *Rhesus* by the attic dramatist Euripides. This is still an open research topic in classical philology. Our idea is to test whether the distribution (in the sense of mathematical statistics) of word categories in the text of *Rhesus* differs significantly from the distribution in the whole work of Euripides.

To do this, we formulate an "axiom of style": a typical distribution can be assigned to every author, and any text written by him follows this distribution up to a deviation which is statistically irrelevant.

Experiments have shown that two different authors differ in their very own way to distribute word categories in their text. They consequently can be distinguished by computing a distribution of word categories that is typical of their works. Furthermore, the typical distribution for a single author is especially influenced by two facts:

- the literary type of the text
- the author's age and changes in writing style throughout his lifetime

From this observation it follows that there is no typical distribution EURIPI-DES'S entire works, but only for texts from several limited temporal periods of his total production time.

1.2 An idea for implementing a solution

Therefore, if we want to use this method of stylometry to test *Rhesus* against the rest of Eurippes' dramatic texts, we have to try and find the different stylistic periods in his work and then to compare the distribution found in *Rhesus* with the distribution during each period.

For the Greek text we use the edition according to the *Thesaurus Linguae Graecae* developed by the University of California at Irvine. So all desired texts are available in digital form. To count the categories in each text we have implemented a so called "Part of Speech Tagger" for attic Greek which can be adopted to any other language.

2 Part of Speech Tagging

2.1 Mathematical Foundations

In order to count categories of any text, we need to solve the problem of assigning a sequence of categories to a given sequence of words, i.e. to the sequence of words forming the text actually under investigation.

Using a part of speech tagger, for any given sequence $W := (w_1, \ldots, w_K)$ one can estimate the probability of all possible sequences $C := (c_1, \ldots, c_K)$ of categories for W. In part of speech tagging a special sequence C is a solution for W if and only if it maximizes the probability

$$P(C_1 \dots C_K | w_1 \dots w_K) = \frac{P(w_1 \dots w_K | C_1 \dots C_K) \cdot P(C_1 \dots C_K)}{P(w_1 \dots w_K)}.$$

$$(1)$$

This says that we search for the sequence (c_1, \ldots, c_K) that it most probable when the sequence of words (w_1, \ldots, w_K) is considered. In other words, (1) is an optimal approximation to the grammatically correct sequence of categories valid for W.

Due to the enormous amount of data neccessary for the computation of the probabilities involved in the term described above, it is impossible to compute a solution directly via this formula.

But to get this complexity under control, we may assume that

1. for any i in (c_1, \ldots, c_K) only the n+1 next categories are dependent of each other, which means that

$$P(c_i|c_{i-1}...c_1) \approx P(c_i|c_{i-1}...c_{i-n})$$
 (2)

2. for any i in (w_1, \ldots, w_K) , the category c_i assigned to w_i is not dependent of the preceding and succeeding categories. So we have

$$P(w_1 \dots w_i \dots w_K | c_1 \dots c_K) \approx$$

$$\approx P(w_1 \dots w_{i-1} | c_1 \dots c_{i-1}) \cdot P(w_i | c_i) \cdot P(w_{i+1} \dots w_K | c_{i+1} \dots c_K) = \prod_{1 \le i \le K} P(w_i | c_i)$$

$$(3)$$

Using (2) and (3), we now have found an approximation for $P(w_1 \dots w_K | C_1 \dots C_K)$:

$$P(w_1 \dots w_K | C_1 \dots C_K) \approx \prod_{1 \le i \le K} P(C_i | C_{i-1} \dots C_{i-n}) \cdot P(w_i | C_i)$$

$$(4)$$

As it is known from probability theory, (4) is the defining equation for a Hidden Markov Model (HMM). From the viewpoint of automata theory, one can understand a HMM as a stochastic finite state automaton (FSA). For HMMs there exist algorithms for an efficient solution for (4). All data we need, are the following two tables:

- one table for $P(c_i|c_{i-1}\ldots c_{i-n})$ (n-gram probabilities)
- and one for $P(w_i|c_i)$ (lexical probabilities)

It takes a long time to achieve this, because there is no Greek lexicon anywhere that contains the lexical probability of each of its entries; and, because the n-gram probabilities are unknown for any n.

To get these neccessary probabilities, we have tagged manually three texts out of the corpus of Euripides, namely *Medea* (431), *Electra* (413), and *Orestes* (408), in order to cover the entire production time of Euripides still available to us. Therefore, including one early, one out of his middle period, and one late tragedy, we have been able to compute trigram-probabilities for Euripides from a sample that is large enough to get reliable estimations, and that on the average should be typical for the overall style Euripides used in his plays.

For the evalution of lexical probabilities we used the manually tagged texts to create a small electronic lexicon of Greek used by Euripides. This lexicon is annotated with the lexical probability for each entry. Every possible category is considered. Because of this, each entry in the lexicon is stated in list form containing as the first element the Greek word and, as succeeding elements, all possible categories annotated with the adequate lexical probability.

As this lexicon does not contain the entire vocabulary appearing in Euripides's texts, we certainly have to address the problem of unknown words in the tagging process, if the whole work of Euripides is to be tagged for statistical evaluation. For unknown words no lexical probability can be found in the lexicon. So how can one compute a solution for (w_1, \ldots, w_K) , if any word in this sequence is unknown? On the other hand, Euripides uses many words only once or twice. Thus many frequencies, and therefore lexical probabilities, are very low. This observation is equally true for the trigram probabilities.

Common part of speech taggers for modern languages such as English use about two million words to compute trigram and lexical probabilities. As EURIPIDES' works have a total of only ca. 170,000 words, the technique described above to solve the problem of sparse data cannot be used in our case.

Under these conditions we still have to develop and implement some different techniques in order to work with sparse data. Surprisingly, when thinking about the theory of tagging as outlined so far, it is a remarkable fact that no linguistic, grammatical or syntactic information is used for tagging other than the two tables of probabilities. However, when reading text in any language every human makes immense use of this kind of information in the process of syntactically and semantically analyzing the sentences one after another. So a part of speech tagger should also employ the additional information given by the linguistic structure of any well-formed sequence of words (This can be a sentence, but also a sequence of sentences).

3 Tagging with feature value pairs

The first step in this direction has been taken by André Kempe ([14]): Words do not only carry information about their own category, but also about gender, number, case, person, etc. This linguistic information plays an important role in the solution to our category problem. Therefore, if we could devise a tagging algorithm that uses this information, we certainly could improve the tagger's precision.

"Part of Speech Tagging" is defined as a process that assigns tags denoting a word's part of speech to the considered word. Up to now, the notion of "part of speech" has been equal to "word category". From now on, we do not simply consider tags which do not only represent the word's category, but also tags which encode a list of so called feature value pairs. These pairs represent all linguistic and syntactic information contained in a given word.

As an example, consider the word

παιδεύομεν.

It contains the following information:

- first person
- plural
- indicative
- present tense
- active

All of these linguistic facts are coded in a tag appropriate for this word. Formally we write a tag as

$$t_i := \bigoplus_{k=1}^{l_i} f_{i,k}, \quad (l_i \text{ is the number of feature value pairs of } t_i)$$
 (5)

If $(t_1 \dots t_i \dots t_n)$ is a sequence of such tags, the probability $P(t_i|t_{i-1} t_{i-2})$ is computed in the following way:

$$P(t_{i}|t_{i-1} t_{i-2}) = P\left(\bigoplus_{k=1}^{l_{i}} f_{i,k}|t_{i-1} t_{i-2}\right)$$

$$= \frac{P\left(\bigoplus_{k=1}^{l_{i}} f_{i,k} \wedge t_{i-1} t_{i-2}\right)}{P(t_{i-1} t_{i-2})}$$

$$= P\left(f_{i,1}|t_{i-1} t_{i-2}\right) \cdot \prod_{k=2}^{l_{i}} P\left(f_{i,k}|\bigoplus_{k=1}^{l_{i-1}} f_{i,k} \wedge t_{i-1} t_{i-2}\right)$$
(6)

For lexical probabilities we now write:

$$P\left(w_i \middle| \bigoplus_{k=1}^{l_i} f_{i,k}\right) \tag{7}$$

There are two major advantages to this approach. First of all the sparse data in the case of trigram probablities are more dense now. In addition, we can save a lot of storage space and execution time during tagging. For further information, the reader is referred to [14].

4 Tagging with morphological analysis

Kempe's idea is very well suited for improving the tagger's precision in the case of trigram probabilities. Unfortunately there are many inflected forms in Greek which induce low frequencies for any lexical entry being an inflection. Feature value pairs do not provide a solution to this problem. Therefore, another idea is to be found, when the frequencies of lexicon entries are to be increased.

Analogously to Kempe's approach additional information should be easily retrievable from the words in the text to be tagged. But with this consideration in mind, a straightforward solution can be found: The inflections themselves carry all information neccessary for determining which word form they represent. Thus, we only need to split every word into its three defining parts:

The prefix appears in the Greek past tenses only. It must be split from the stem, but carries no information not already contained in stem and suffix. This idea leads to a change in the representation of our lexicon. As the stem is the only characteristic part of a word (prefix and suffix are both exchangeable by the rules of inflection which the Greek grammar defines), our idea is to store the word's stem alone in the lexicon. Prefix and suffix are then to be stored in two different tables.

All words that are not inflections, but have categories such as preposition or particle, are stored in the lexicon unchanged as full forms. Thus, in this case, there is no difference between tagging with or without morphological analysis.

The fact that in most cases lexicon entries are stems only – except for full forms – has a severe impact on the computation of lexical probabilities. Since words are split into stem and suffix their lexical probabilities cannot be computed in the same way as before. The lexicon now only contains the lexical probability of the stems that can be valid for a given word. On the other hand, as shown above, an additional table is required which contains the lexical probabilities of all suffixes. By table lookup we can determine the lexical probabilities of the suffixes valid for a given word. Consequently, given the word w with stem s and suffix u (w = su) we have two probabilities now:

- 1. $P(t_i|\text{stem} = s)$, where $1 \le i \le n_s$ and n_s is the number of tags for stem s, and
- 2. $P(t_j|\text{suffix}=u)$, where $1 \leq j \leq n_u$ and n_u is the number of tags for suffix u.

Assuming independence of these two probabilities, we write:

$$P(t_i|\text{stem} = s) \cdot P(t_j|\text{suffix} = u) =$$

$$= P(t_i|\text{stem} = s \land \text{suffix} = u) =$$

$$= P(t_i|w) \approx P(w|t_i)$$
(8)

The last step is due to Bayes' rule¹. Of course, step 2 is valid if and only if suffix and stem form a correct Greek word. For example,

$$\pi\alpha\delta\epsilon\dot{v} - \sigma\alpha\nu\tau o\varsigma$$

is correct, while

$$\pi\alpha\delta\epsilon\dot{v}\sigma\alpha\nu\tau - o\varsigma$$

is not. But in both cases the suffixes are correct. Therefore, during the computation of lexical probabilities there must be a check to determine whether the computed probability is valid at all.

There are some advantages with this approach concerning the computation of lexical probabilities:

^{1[13]} shows that in the case of part of speech tagging both formulas are almost equivalent.

- Frequencies for stems and suffixes are higher when considered separately. Thus, tagging precision can be further increased.
- In the case of unknown words, enough information can be extracted from the suffix to significantly limit the number of tags possible for the given word compared to the total number of tags. Taggers commonly consider all tags possible for any unknown word. Thus, morphological analysis vastly increases the precision of lexical probabilities during tagging.
- No lexicon for full forms is neccessary. For highly inflected languages, this means an enormous decrease of resources needed for lexicon storage and access.

5 Implementation

For our task of tagging the corpus of EURIPIDES we implemented the morphological analysis using regular expressions which describe almost all of the suffixes of the Greek language and the associated tags. On the basis of these regular expressions we implemented a parser that precedes the tagging process and annotates all words with their possible tags and respective lexical probabilities. This parser is implemented in C. As everything, and especially all data, had to be built from scratch, this seemed to be the most appropriate way to reach our goal. But morphological analysis could be achieved in quite a different way, too.

Our complete tagging system was trained with ca. 17,000 words (see above) and works with an average accuracy of about 96,6%. The lexicon has about 5,900 entries. Due to different accentuation marks possible for the same stem, some of these entries actually occur twice. So the number of different Greek words stored in the lexicon is even lower.

Another point to be made here is the fact that many other modern languages form words by inflection and suffixes giving the stem a special meaning and denoting special categories or tags in every case. From this point of view it becomes clear that morphological analysis is a powerful tool for part of speech tagging not only for ancient Greek. Here are some examples for suffixes in English, German, and Italian:

German	English	Italian
-ig	-ness	-ista
-ung	-ize	-tore
-heit	-ate	-trice
-en	-tion	-tá
-er	-ing	-ndo
-el	-ed	-bile
-erin	-ly	-mente

6 Application to the corpus of Euripides

6.1 Statistics

First we used our tagger to create tables which count the number of words in each category for all eighteen works of Euripides that are not lost during the tradition of the ancient texts including the critical *Rhesus*.

On the basis of these data we try to give answers on the questions posed in section 1. To measure the extent to which a certain work deviates from the distribution of several others, we use the χ^2 -test with two classes:

$$\chi^2 := \sum_{1 \le i \le 2} \frac{(M_{i,j} - p_{i,j})^2}{p_{i,j}} \tag{9}$$

 $p_{i,j}$ is the probability for category j to appear (i = 1) or to not appear (i = 2), while $M_{i,j}$ is the number of words of category j (i = 1) or the number of words of category different from j (i = 2).

For every text tested we compute the sum of all significant deviations α_i and measure their distance from the common mean value μ in respect to the common standard deviation σ by

$$\rho_i := \frac{\alpha_i - \mu}{\sigma} \tag{10}$$

 μ and σ are estimated by Maximum Likelyhood Estimation. ρ_i is considered significant if and only if $\rho_i \geq 2$.

6.2 Results

In the corpus of Euripides there are several works whose date of creation is supposed to be between 413 and 408, *Helena*, *Ion*, *Iphigenia Taurica*, and *Phoenissae*. In a first series of tests we searched for significant deviations between these four works. None could be found. However, the value for deviation became larger, though still unsignificant, when taking into account *Electra*, too. But *Orestes*, on the other hand, seems to match smoothly into the pattern defined by the other four texts. From these observations we conclude that *Electra* could mark the transition from the middle to the late period of Euripides' work. But we have not discovered any new facts which could make clearer the time of writing of the other four works considered in these tests.

Next we tried to find a transition from the early to the middle period. To do this, we tested *Alcestis*, *Medea*, and *Heraclidae* against several works from the middle and all from the late period. All proved to deviate significantly. So, by means of this test, they are characterized as early works. For *Hippolytus* in the first attempt we could not find a significant deviation. But, after exchanging the possibly spurious *Rhesus* with *Helena* out of the late period and *Hecuba*

with *Electra*, we received significant values for *Hippolytus* as well. Therefore, we believe that *Hippolytus* and *Hecuba* mark the transition from the early to the middle period. This stylistic characterization of Euripides' work coincides precisely with its chronological order.

In a final series of tests we wanted to find out something about the behaviour of *Rhesus*. First we found a significant deviation from the early period.

As an example, we show a table containing the evaluation of the test which compares Rhesos and the early plays listed below (The first column contains the names of the different word categories considered. The last row shows the values for ρ . All other numbers are χ^2 -values.):

	Alcestis	Medea	Heraclidae	Hippolytos	Hecuba	Rhesus
adjk	0.0909	1.79	1.28	0.911	0.0500	0.922
adjp	21.7	15.7	9.48	0.846	6.57	0.188
adjs	3.37	5.77	0.270	0.647	4.31	3.67
adva	0.117	2.60	1.63	4.98	0.273	0.0796
advs	0.862	0.00389	0.918	0.101	0.171	4.76
arti	0.383	4.97	4.25	4.30	2.72	11.1
depn	0.567	0.0849	20.1	1.52	1.59	7.17
idpn	0.0684	0.00189	0.154	0.0707	0.957	0.558
intj	4.98	0.176	0.122	13.9	3.93	21.3
irpn	2.48	0.0970	0.600	0.174	1.11	0.292
konj	1.22	2.70	0.165	3.63	2.96	0.0217
name	8.06	31.9	2.07	11.9	14.7	69.0
nega	3.66	0.257	0.171	2.10	4.65	1.29
nume	0.0149	0.0132	0.000453	5.49	1.48	1.40
parl	3.78	0.629	7.44	3.58	7.69	10.8
part	4.67	5.51	0.278	7.47	0.0921	13.3
pepn	3.94	0.801	0.00385	0.357	0.193	3.76
popn	0.252	2.59	2.84	0.371	1.18	7.18
prae	0.459	5.07	2.07	0.233	0.0918	8.72
repn	0.110	0.346	0.482	0.00170	0.00852	1.51
rlpn	0.0156	2.56	3.01	0.165	0.987	0.775
subs	1.96	1.04	11.2	5.11	3.92	13.3
verf	5.17	0.168	0.0111	0.00109	0.853	0.542
veri	0.693	0.00435	5.10	2.26	5.02	1.20
	-0.870	-0.124	-0.124	-0.124	-0.870	2.10

The value of 2.10 for *Rhesus* indicates that there are significantly many deviations of the χ^2 -values for *Rhesus* compared with the overall mean values. This says that in the text of *Rhesus* too many word categories appear in too small or too large a number in order to be still characteristic for the typical numbers of appearances in the other texts included in this test. From this result we conclude that *Rhesus* has not been written at the same time as the other five plays.

We got the same result when testing the middle period only and both early and middle periods.

Only when compared with the late period, does Rhesus show no significant deviation at all.

We therefore conclude that, when using our "axiom of style" as a criterion, the hypothesis of *Rhesus* being a early or middle-period-work by Euripides can be rejected. However Euripides could still have written *Rhesus* in his late period or even before 438. Unfortunately, not enough text material from before 438 exists to test *Rhesus* by means of statistical techniques. Nevertheless, the deviations found for *Rhesus* point out to the fact that the time of its writing is strongly restricted to either the very early or very late lifetime of Euripides. The question of authenticity, however, still remains open.

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